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AN EMPIRICAL COMPARISON OF LATENT TRAIT THEORY AND

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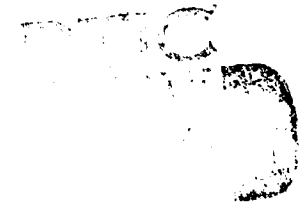
MEASUREMENT OF JOB SATISFACTION

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Data were collected on the Job Descriptive Index from a large heterogeneous sample of respondents. These data are used to compare empirically a latent trait model to a hierarchical factor analytic model. Latent trait item parameters estimated by LOGIST agress quite well with the item loadings on a general satisfaction factor based on the methodology suggested by Humphreys. These results are consistent with a hierarchical job satisfaction construct that has one general factor and multiple group factors. The implications of the results and future research are discussed.

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Abstract

Data were collected on the Job Descriptive Index from a large heterogeneous sample of respondents. These data are used to compare empirically a latent trait model to a hierarchical factor analytic model. Latent trait item parameters estimated by LOGIST agree quite well with the item loadings on a general satisfaction factor based on the methodology suggested by Humphreys. These results are consistent with a hierarchical job satisfaction construct that has one general factor and multiple group factors. The implications of the results and future research are discussed.

Scientific inquiry into the meaning and measurement of job satisfaction must inevitably consider the structure and complexity of the construct. One aspect of structure is the relation of item responses to the construct; or a theory of measurement. Latent trait analysis and factor analysis provide two diverse methods for studying this structure. Because the former approach has received little attention in the job satisfaction literature, and the latter usually leads to confusion, both will be described briefly and some recommendations made.

Both methods depend on responses to a large set of items that are suspected to relate to job satisfaction. Both result in a model that specifies the relation of item responses to the construct of job satisfaction. But at this point, the two methods diverge. Briefly, Mulaik (1972, p. 96) states that "factor analysis is a formal model about hypothetical components which account for linear relationships that exist between observed variables." He also describes the following assumptions of the model. First, the hypothetical component variables form a linearly independent set of variables. Second, the component variables can be divided into common components that relate to more than one observed variable, and unique factors that relate to only one observed variable. Third, common factors are always assumed to be uncorrelated with unique factors and unique factors are usually assumed to be mutually uncorrelated. It is also assumed that there are fewer common factors than observed variables.

In contrast to this linear model, the latent trait model assumes the relation between the hypothetical construct and observed response is best expressed in probabilistic terms. The normal ogive curve describes the

relation between the amount or degree of the construct that a person has and the probability of making a particular response to a questionnaire item. It is assumed that the responses are locally independent or the probability of making a correct response is not affected by the answers to other items. Finally, most applications to date have assumed that the construct is unidimensional. Further description of the model appears later in this paper.

The primary difference between these two models is that the factor analysis model assumes a linear relation between an observed variable and a (possibly) multidimensional construct, whereas latent trait theory posits that the observed variable (item response) is curvilinearly related to a (usually) unidimensional construct. Besides differences in models there is also a difference in methods of estimation. Most factor analytic work depends on extraction of independent components followed by transformation to some mathematical or other criterion. On the other hand, recently developed programs for estimating latent trait parameters use maximum likelihood techniques.

In spite of these differences, it should be emphasized that some convergence between these models is expected. In many cases a linear term can provide a good fit to data that actually represent a monotonically increasing curvilinear relation between item response and trait. Therefore, the primary focus of this paper is not so much on the relative validity of the two models, rather the appropriateness of latent trait theory as an alternative and potentially useful model for improving the measurement of job satisfaction.

Factor Analytic Model

Locke (1976) has criticized the widespread use of factor analysis to study the structure of job satisfaction. He argues that deriving statistical dimensions from job attitude questionnaires adds little to our understanding of the construct. In fact, he laments the fact that factor analysis has led to a proliferation of empirical dimensions in lieu of thorough theoretical analysis of the construct (Locke, 1976, p. 1301). Obviously, the number of empirical dimensions can be manipulated by the researcher who writes good items and has access to large samples of tireless respondents. But, there is one point that is often overlooked by both critics and proponents of this factoring perspective. There is a particular, regularly observed, pattern to the elements and dimensions of virtually any job satisfaction instrument. Simply stated, scale scores based on orthogonally rotated factors are almost always correlated positively to a moderate degree. It is lamentable that little attention is given to interpreting these positive correlations or even considering them as the single most obvious and general outcome of any factor analytic study of job satisfaction.

This state of affairs is not restricted solely to factor analytically based research on job satisfaction. Probably the most striking characteristic of matrices displaying the intercorrelations among large and very diverse measures of ability, assuming large samples and reliable measures, is the size of the smallest correlations. The smallest of these correlations are typically positive suggesting the presence of a general factor of intelligence that is frequently hidden or obscured by the extraction and rotation algorithms used by most American researchers.

Humphreys (1962) and Humphreys and Hulin (1979) have commented on the proliferation of factor analytically based measures of ability to the detriment of attention being paid to general measures of ability that are consistent with the broadly based, behavioral observations that gave rise to the construct of intelligence and ability.

Consider the Job Descriptive Index, (JDI) (Smith, Kendall and Hulin, 1969). It is probably the most thoroughly developed and frequently used measure of job satisfaction (Vroom, 1964). The developers of the instrument (Smith et al., 1969) reviewed a large number of previous measures of the construct before deciding on the measurement of 5 facets: work, pay, promotions, superviser, and coworkers. They noted that this list does not exhaust the possibilities, because these facets could have been broken down into more specific job elements. Other relevant job characteristics such as physical environment could also have been considered as facets.

Published factor matrices of the 72 JDI items have been based on orthogonal rotations (e.g. Smith et al., 1969 and Smith, Smith and Rollo, 1974). Correlations among facet scores have been reported to range from .16 to .52 (Smith et al., 1969). These authors explain this range in correlations among supposedly independent facets from both a theoretical and methodological perspective.

The correlations could be caused by common method variance that tends to inflate correlations among variables that are measured via the same instrument. In other words, the facets are theoretically, but not empirically independent. If method variance were soley responsible for these correlations, then this common variance would constitute a methodological bias and is theoretically irrelevant.

On the other hand, the authors offer several theoretical explanations for the correlations such as the hypothesis that satisfying events occur nonindependently. Satisfying things occur together. Smith et al. (1969) suggest that good supervision can affect the other facets and workers' perceptions of them. For instance, a good supervisor may question his/her subordinates about the type of work desired, and then take action to modify the work to meet their desires. This would account for an empirical, as well as conceptual association between these two facets of satisfaction. Another possibility is the spillover effect. Workers that are very satisfied with their pay may distort their perceptions of other job facets to be consistent with their pay satisfaction. Smith, et al. also speculate that the magnitude of the correlations among facet scores might be affected by the objective job and organizational situation. For instance, if pay is directly tied to promotion, due to company policy, then satisfaction with these two facets should be highly correlated.

From a structual point of view, these correlations among facet S across may or may not be considered by a factor analyst. One perspective is to treat them as nuisance effects that complicate our multivariate analyses. Another perspective is to develop an oblique factor model that explicitly incorporates these correlations. However, this is where the options become almost limitless and the researcher must apply some psychological sense to the choice of methods.

To make this issue clear, consider again research on the structure of human intelligence. Because there are a wide range of factor extraction techniques, criteria for number of factors, and rotational schemes (see Harman, 1967, for a description) there have been diverse interpretations of

the nature of human intelligence. One major issue in this debate has been the number of primary factors (or basic elements) of human intelligence. On the one hand, Guilford (1967) has proposed a Structure of Intelligence composed of 120 primary mental abilities. Humphreys (1962, 1979) has criticized this structure because the large number of hypothesized abilities may be more a function of the factor analytic procedures used by Guilford and the specificity of the tests that were analyzed, than the basic mental capacities of humans. Humphreys' (1962) and Humphreys and Hulin's (1979) alternative to this emphasis on very specific tests is a model of human intelligence and corresponding factor analytic procedure that is based on the general rather than specific nature of intelligence. This model is called the hierarchical factor model. It posits that there exists a general factor of intelligence that is responsible for the positive correlations among tests of narrower abilities. This general factor is a heterogeneous blend of abilities and skills that appears whenever a variety of ability, aptitude, and achievement tests are administered in a wide range of talent (Humphreys, 1979). Due to its heterogeneity, it has predictive validity for a wide range of human performance either in school or work.

Early work on a related factor model was conducted by Holzinger (1936). He developed the bi-factor method of factor analysis as an extension of Spearman's restrictive two factor theory of human intelligence. Harman (1967) gives a thorough description of the bi-factor techniques. The model essentially accounts for each observed variable's variance as the sum of general factor variance, one group factor variance, and unique variance. In other words, if z is the observed variable, F_0 is the general factor, F_1, F_2 ... . F_n are n group factors, and U is the unique component, then for

variable 1 the model states

$$z_1 = a_{10}F_0 + a_{11}F_1 + U_1$$
$$z_1 = a_{10}F_0 + a_{11} + U_1$$

The common variance of an observed variable is broken into the two common factors only, F_0 (the general factor) and F_1 (the group factor). An example, a pattern matrix of a 10 item test measuring two correlated facets of satisfaction, would then look like Table 1.

Table 1 About Here

In this case, the observed correlations among items are relatively large within a scale, and small (but certainly non-zero) between scales. The general factor accounts for these small correlations.

More recently, Humphreys (1962) has described methods based on higher order factoring (Harman, 1967) that yield essentially the same structure in many cases. In general, orthogonal factors are extracted through any of a variety of methods. Rarely do these factors have any psychological meaning. Therefore, they are rotated to the principle of simple structure (Thurstone, 1947).

Oblique factors normally give the best approximation to simple structure, but psychologists now are faced with the problem of interpreting correlated factors. Higher order factoring can help to resolve this problem. Second order factors can be extracted from the correlations among the first order factors. If one factor is sufficient to describe the correlations, then this factor represents the general factor. If more than

one factor is present in the second order, then third order factors may be necessary to uncover the general factor. For simplicity, assume that one second order factor is sufficient.

Upon resolving the number and order of the factors, Humphreys suggests use of a further transformation. Briefly, Schmid and Lieman (1957) developed a transformation that is applied to the oblique first order factors. The transformation is based on the loadings of the first order factors on the higher order factors. Essentially, the oblique factors are transformed to orthogonal factors and the general factor becomes part of the structure matrix to account for the relation among oblique factors. This transformed matrix is easily interpreted because all factors are now orthogonal. This hierarchical factor model is contrasted to the more usual common factor model by its explicit specification that all observed variables are in part explained by one general factor. Further factors represent the group factors and account for only a subset of the observed relations among variables. Of course, in both models all observed variables also have a unique component consisting of specific factors and measurement error.

These developments are appropriate for job satisfaction data as well. If the correlations among first order factors are indeed represented well by a general satisfaction factor, then perhaps the hierarchical structure is a logical alternative to the pseudo-orthogonal structure that is normally used to represent the construct. The importance of this factor in studies of job satisfaction remains to be seen.

Latent Trait Model

In contrast to factor analysis, latent trait theory has a much shorter history of application to job satisfaction or attitudes in general. In fact, except for some related models developed by by Lazarsfeld and described in Lazarsfeld and Henry (1968), there has been little attention given to it. Latent trait theory or item characteristic curve theory (Lord, 1975), specifies a much different model of psychological measurements than that represented by classical test theory.

A latent trait model is a mathematical statement of the probability of a response pattern to test items. This probability is expressed in terms of functions called item characteristic functions and a single (unidimensional or multidimensional) trait of the respondent. An item characteristic function gives the conditional probabilty that a randomly chosen person from the population of all people at a given value of the trait answers the item correctly (or affirmatively in the case of attitude measurement). The notation commonly used denotes the trait by Θ, and the item characteristic function (graphically represented by the item characteristic curve or ICC) for the ith item by $P_i(\Theta)$.

In virtually all applications to date, theta is assumed to be unidimensional. $P_i(\Theta)$ is given by the formula

$$P_i(\Theta) = 1/[1 + \exp(-A_i D(\Theta - B_i))].$$

The numbers A_i and B_i are called item parameters with A_i reflecting item discrimination and B_i reflecting item difficulty. D is a scaling factor usually set to 1.702. A powerful assumption commonly made in latent trait

theory permits the specification of the probability of a pattern of responses. The assumption of local independence asserts that the item responses are conditionally independent. This means that the conditional probability of a response pattern, say for example U = (0 0 0 1 1 0) of a 6 item test or questionnaire, can be written as a product. The formula is as follows:

$$P_i(U|\theta) = \prod_{i=1}^{n} P_i(\theta)^{u_i} (1 - P_i(\theta))^{1-u_i}$$

U is a vector of item responses. The ith term of the U vector is the item response for item i and equals 1 if the item response is correct and 0 if the response is incorrect (this format applies to ability tests, but the generalization to satisfaction scales readily follows).

The choice of an appropriate model depends on the application. The current two-parameter model is actually a specific form of the more general three parameter model advocated by Lord (1970). This three parameter model assumes that the ICC will differ on difficulty (B_i), discrimination (A_i), and the lower asymptote (C_i) (not shown), sometimes called the correction for guessing. In the measurement of job satisfaction, it can be argued that the lower asymptote for the curve should be 0. In other words, as the level of theta approaches $-\infty$, or no satisfaction, the probability of responding positively to a satisfaction scale item approches 0 because "guessing" does not occur, and there is no obvious analogue to guessing in satisfaction assessment.

In contrast, for a multiple choice aptitude test item, as theta approaches $-\infty$, the probability of answering correctly is still approximately 1/n where n is the number of response alternatives. Theoretically, even a person with no ability could guess the correct answer for an item. But a person with psychologically zero job satisfaction should not respond positively to an item if the model is correct. Thus, the present use of the two parameter model is a special case of the three parameter with all c_i set to 0.

A major question concerning the use of latent trait theory in the measurement of job satisfaction is the multivariate nature of relevant data. If the data reflect the complexity of the construct (multidimensionality), then what is it that the latent trait model is estimating? There is some empirical research that is relevant to this issue.

A number of studies have investigated the effect of multivariate data on item calibration in the one-parameter logistic model. Not surprisingly, this logistic model fit simulation data from a one factor test better than either two factor or three factor test data (Reckase, 1972). Of particular interest is the finding that the three factor test data was fit better than the two factor data indicating that the relationship between factorial complexity and fit of the model is not a simple one. Forbes and Ingebo (1975) showed that the item parameters calibrated from a heterogeneous ability test (3 homogeneous subtests) were ordered similar to the item parameters estimated from the homogeneous subtests alone. Though not directly relevant to the application of the more general latent trait models (two and three parameter) these results do indicate that factorial complexity will have varying and perhaps unknown degrees of effect on item

parameters.

More directly relevant are studies by Hambleton (1969), Hambleton and Traub (1973), and Reckase (1979). The first two studies (Hambleton, 1969; Hambleton and Traub, 1973) found that the two and three parameter model fit multidimensional data better than the one parameter model. Again this is not surprising because additional parameters in any model invariably increase the fit of the model to a sample of data. More important is the generalization, first suggested by Hambleton (1969), that the average discrimination value $(\bar{A}_i)$ is positively related to the size of the first factor. Reckase (1979) studied this issue in 16 samples. He used both empirical data and simulation data that had varying degrees of factorial complexity. He found that the correlation between $\bar{A}_i$ and the eigenvalue of the first principal component was .97. He also reported that the size of the first principal component accounted for 63% of the variation in the fit of the model to the data in the samples.

This raises the question what, to repeat, is the latent trait being estimated when there is no dominant first factor? Reckase (1979) also addressed this question by generating simulation data from five independent factors. He reported that the A_i values estimated from this sample correlated highly with the loadings from one factor (.92) but were unrelated to the other four factors. The correlation between A_i and the unrotated first principal component loadings was .55. This result, in conjunction with previously reported results, suggests that in data with one dominant factor and several other smaller factors, the item parameters will be based on the first principal component. When none of the factors are dominant, the parameters are based on only one of the factors. The characteristics of

this factor that distinguish it from the others has not yet been determined.

Although Reckase's (1979) results seem especially appropriate to the estimation of item parameters in multivariate job satisfaction data, there were several features of his data that are not likely to be present in job satisfaction data. First, his simulation studies were based on items that had very high communalities. Items loaded either .7 or .9 on the theoretical factors. Also, these loadings were uniform for all items. Items in job satisfaction questionnaires are likely to have lower communalities and a range of values. Another difference is that he used data from mental aptitude tests that are likely to be approximately multivariate normal. In his simultion data, the distributions were not reported. In contrast, job satisfaction data tends to be negatively skewed. This difference could also affect parameter estimation and the similarity between factor loadings and discrimination parameters. Finally, Reckase's comparisons were made between discrimination parameters and loadings on the first principal component, not the general factor from a hierarchical analysis. The effect of the transformations to the hierarchical solution has not been demonstrated.

In comparing hierarchical factor analysis and latent trait theory the present study primarily addresses the feasibility of applying latent trait theory and available parameter estimation procedures to the assessment of job satisfaction. However, a necessary preliminary question involves the application of hierarchical factor analysis to job satisfaction data. Does this analysis result in a psychologically meaningful structure that illustrates the presence of a general satisfaction factor and its relation to item responses? The second question presupposes a positive answer to the

first and asks: do the latent trait A parameters estimated from job satisfaction data converge with 1) the factor loadings on the general factor and 2) the factor loadings on the first principal factor?

METHOD

Sample

The data used in this study were obtained from two larger research projects. The first involved responses from individuals in the Illinois Army National Guard and the Illinois Air National Guard. The second project involved responses from workers in a retail sales organization.

For the first project, questionnaires were administered by members of a University research team. The researchers met the guardsmen at armories during weekend drill sessions. Though circumstances varied, surveys were usually administered in classrooms to groups of 10 to 30 guardsmen. Since the survey data were to be used to predict individual turnover decisions, (See Hom and Hulin, 1978) questionnaire identification was requested. A total of 2657 useable questionnaires were obtained from 74 units across the state of Illinois (56 from the Army National Guard and 18 from the Air National Guard). Though participation was not anonymous, the researchers did emphasize that it was voluntary and confidential. Only members of the research team had access to individual questionnaire responses.

In the sample, 96% were male, 83% white, and 87% were high school graduates. The average age was 28 years and 66% of the guardsmen were married. Further description of the original sample, questionnaire, and results are presented by Hom and Hulin (1978) and Katerburg and Hulin (1978).

Further data were obtained from questionnaires that were administered during a second research project. This sample consisted of non-managerial personnel in a large international merchandising company. Useable questionnaires were received from 1632 employees distributed among 41 units from around the country. In contrast to the first project, the surveys were administered by organization staff rather than independent researchers. Participants completed the surveys on company time and mailed them to the researchers. Again, identifying informtion was requested. However, though the cover letter on the questionnaire emphasized the confidential and voluntary nature of the responses, it is quite probable that the presence of organizational staff increased the doubts about the privacy of responses.

In this sample, 59% of the respondents considered themselves full time workers and the other 41% were part time. Thirty percent of the sample was male and the average education was 12.7 years (slightly more than high school). The average age was 36.5 years and average tenure was 6.62 years. Further description of this sample, questionnaire and results can be found in Miller (1979).

Selection of Data

The Job Descriptive Index (JDI) (Smith et al., 1979) was used as a measure of job satisfaction. The JDI is a series of adjective checklists that assesses satisfaction with the work itself, pay, promotional opportunities, supervisor, and coworkers. The five scales of the JDI contain a total of 72 items. In the military sample, only 4 scales were included in the questionnaire (9 items omitted). Also, 3 adjectives on the coworkers scale were altered in the same sample. A total of 12 JDI items

were not included in the analysis of the military data. Therefore, 60 items from the JDI were used to index job satisfaction in the military sample, while the full 72 item version was available for the civilian sample.

Due to the large amount of available data (4289 respondents in the 2 samples combined), it was possible to select data that avoided a potential computational problem without severely limiting the size of the sample. For the current study, only subject records with no missing data on the 60 JDI items were included. Although Lord (1974) has an acceptable solution for estimating both item and θ parameters for aptitude tests with omitted responses, it is based on assumptions that clearly are not tenable for responses to the JDI. For instance, Lord (1974, p. 250) states the assumption that "examinees wish to maximize their expected scores and that they are fully informed about their best strategy for doing this." Moreover, it is much more common for respondents to omit the items from one scale rather than sporadic omitting of individual items. After eliminating records with omitted responses, the sample consists of 3813 response records (2463 = military, 1350 = civilian).

The response records were divided further. First, a representative sample was selected to estimate latent trait item parameters. Every other record was chosen (n=1906) in order to reduce required computer time while maintaining the generality of the results across both military and civilian samples. Thus, the latent trait parameters were to be based on responses from 1231 military personnel and 675 retail store workers.

Rather than using the same sample of records for deriving the hierarchical factor structure, only the records from the retail personnel were used. This decision was based on the desire to use all five JDI scales

to estimate the general factor. This also allows for direct comparison to previous factor analytic studies of the JDI such as those by Smith et al. (1969). Therefore, the factor analysis was conducted on 1350 responses to the JDI from the retail personnel. For this analysis, the formula scoring routine from Smith et al. (weights of 0, 1, 3) was retained.

Parameter Estimation

Parameters for the latent trait model were estimated from the maximum likelihood algorithm (LOGIST) developed by Wood, Wingersky and Lord (1976). LOGIST requires dichotomous scoring of items with 1 indicating satisfaction and 0 indicating no satisfaction. The responses scored 0 or 1 by the Smith et al. (1969) procedure were transformed to 0. Responses that would have received a 3 were transformed to a 1. The justification for this adjustment comes from Smith et al.'s results demonstrating that question mark responses (scored 1) were more frequently given by individuals with low satisfaction.

All factoring was based on the 72 item correlation matrix with squared multiple correlations in the diagonal as communality estimates (referred to as the reduced correlation matrix). The first principal factor was extracted by the principal axis method (Harman, 1967).

For the hierarchical factor analysis, principal factors were extracted initially from the reduced correlation matrix. The eigenvalues of the first 10 factors appear in Table 2. Though 6 factors had eigenvalues greater than 1, 5 factors were rotated based primarily on the assumption that one factor would represent each facet of satisfaction. The five factors were then rotated obliquely using the BINORMAMIN procedure (Kaiser and Dickman, 1977). The correlations among these factors, which appear in Table 3, formed the basis for the second order factoring.

Tables 2 and 3 about here

The second order principal factor was extracted from a reduced correlation matrix of first order factors. Since poor communality estimates might result from squared multiple correlations based on only four factors, an iterative procedure was chosen for estimating communalities and one principal factor (Harman, 1967). The loadings of the 5 first order factors on the resulting second order factor appear in Table 4. These loadings were then used to construct a matrix for transforming the five oblique first order factors into an orthogonal, hierarchical configuration with one general factor and five facet factors. This matrix, which appears in Table 5, is constructed in the following manner. The loadings of the five first order factors on the one second order factor (h_1) compose the first column of the transformation matrix. The remaining five columns represent a diagonal matrix with $\sqrt{1-h^2}$ as the diagonal entries. This matrix is then premultiplied by the factor pattern matrix from the BINORMAMIN rotation. The reader is directed to Schmid and Lieman (1957) for the specific procedures and rationale.

Tables 4 and 5 about here

Results

Table 6 presents the A_i values from the latent trait analysis, the loadings on the first principal factor, and the loadings on the general factor as well as the 5 facet factors from the hierarchical factor matrix. One criterion for evaluating the interpretabilty of the hierarchical matrix

is by its similarity to the desired simple structure (Thurstone, 1947). In the hierarchical model, an item should have non-zero loadings on both the general factor and on the appropriate facet factor. For the other 4 factors, the loadings should be zero or "vanishingly small." The total number of elements in the matrix is 432. Of these, 432 - 144 = 288 should be near zero. If all loadings less than or equal to .10 are considered vanishing, then 267 or 92.7% of the loadings that are supposed to vanish, do vanish. For comparative purposes, six principal factors were rotated orthogonally using VARIMAX. This solution (not shown), which was without the general factor, resulted in only 175 or 60.8% of the loadings vanishing. If five principal factors are rotated orthogonally, the results are that 251 or 87.1% of the loadings vanish. The results of the BINORMAMIN rotation of 5 factors yielded 250 or 86.8% of the loadings as vanishing.

Table 6 about here

Another principal of simple structure is that the factors be defined by more than one observed variable. This was obviously the case for all factor solutions (except the six factor varimax solution) as each factor was defined by the items within one JDI scale.

The convergence of the factor analytic loadings and the latent trait parameters can be assessed by correlations. However, the latter have to be transformed because they are exponential in nature. Therefore, natural logarithms of the 60 A_i parameters were computed and compared to the corresponding factor loadings from the two factor analyses. Correlations among these transformed parameters appear in Table 7. The correlation of

.89 between factor loadings from the principal factor and the hierarchical
factor analysis shows a high degree of similarity between the two. For both
general factors the loadings are highly related to the latent trait
parameters ($r = .79$, $r = .77$).

Discussion

The results of the hierarchical factor analysis should be interpreted
in light of the purpose of this paper. Because the structure matrix
provides a pattern that is psychologically meaningful, the loadings on the
general factor do represent a good comparison for the latent trait
analysis. That is, there is little evidence or reason to suspect that item
responding is more complex than the hierarchical solution demonstrates. In
developing a satisfaction scale, items that load on more than one common
factor after an orthogonal rotation are normally eliminated from the
instrument. Therefore, the matrix yields a nice reduction of the 72 item
data that also is psychologically meaningful, and allows comparison to the
latent trait results.

The addition of the general factor to the already moderately well
fitting 5 orthogonal factor solution could be criticized for making the
matrix less parsimonious (more parameters). The obvious response to this
objection is that the orthogonal dimensions have no substance in empirical
observation. Besides, parsimony is not the sole or even overriding goal of
science. If this were the case, then 5 principal factors (without rotation)
would be desireable because they account for the maximum possible variance
with this number of parameters. Another criticism could be based on the
second order factoring rather than simply leaving the factor

intercorrelations to be interpreted. In this case, it can be argued that the higher order factoring is both a more meaningful and parsimonious solution because it involves a reduction of the factor intercorrelation matrix. The Schmid-Lieman (1957) transformation simply uses this reduction to orthogonalize all factors and define them in terms of the observed variables.

The main advantage of the hierarchical factor solution is that it illustrates that items on different scales do share common variance. While this covariance is smaller than that within scales, it is important and should not be ignored through the use of traditional common factor analysis in the Thurstone tradition. This study was not designed to further evaluate the meaning of the first principal component, the general factor, or the five group factors. Simply stated, the hierarchical solution does represent a nice summary of empirical data.

Because of the clear results from the hierarchical solution, the interpretation of the latent trait analysis is clear. The item discrimination parameters are describing the relation of this general factor, however we choose to extract or represent it, to the probability of endorsing the items. Based on Reckase's (1979) empirical results, the size of the first principal factor (Eigenvalue = 11.06) indicated that this would be the case. On the other hand, from the perspective of latent trait theory, there are other obvious θ's that are related to the probability of item endorsement. These, of course, are the scale θ's or facet satisfactions.

The correlation between factor loadings on the first principal factor and item discrimination (A_1's) agrees with previous results (Reckase, 1979).

If these had been aptitude test data with multivariate normal distributions, this would have been a foregone conclusion. However, the point should be emphasized that this current finding indicates that there is nothing inherently different about job satisfaction data that prevent it from being considered in the latent trait framework.

It is felt here that this application of the latent trait approach to job satisfaction was a necessary first step. It was not enough to compute parameters from large amounts of data. The similarity of the latent trait parameters to the hierarchical factor analysis loadings from a somewhat different sample add a great deal to its interpretability. The impact of latent trait theory on the assessment of job satisfaction may not be acknowledged until methods for estimating all parameters in a multivariate latent trait model are developed and applied. However, there are hints in the outcomes of the current study that indicate what this model might look like.

First of all, the essentially bi-factor solution of the hierarchical model strongly suggests that what is now referred to as an item characteristic curve with one axis for θ will be referred to as an item characteristic response surface with two axes for two independent θ's. This means that for some items, if the scale θ is very low, then the probability of endorsing an item may never exceed .7, for example, when the general θ is within the meaningful interval of -3 to +3. On the other hand, if the general θ is very low (-3), a scale θ of +2 may yield a response probability of .9 (arbitrary). In summary, though an improved latent trait model for job satisfaction may be estimated following the development of a multivariate parameter estimation program, the present results give some

evidence as to what this model will be.

At the same time that these data strongly suggest the necessity for developing multivariate latent trait models that will describe responses to each item in terms of both a general and a group or scale θ , it must be emphasized that the appeal of a multivariate model over one that emphasizes and uses only the general factor from the hierarchical solution will depend on the goals of the researcher and the uses to which the resulting scales are to be put. If the aim is the prediction of behavioral responses reflecting general acceptance or rejection of a work situation, such as turnover or absenteeism, then the use of job satisfaction scores reflecting the general factor will probably provide predictive power equal to that generated by a multivariate approach. Humphreys and Hulin (1979) have commented on this in the domain of ability measurement and job performance prediction. Their arguments are appropriate here. The fit of the latent trait discrimination indices, derived assuming local independence and unidimensionality of θ, to the loadings of the items on the general factor from the hierarchical factoring suggests minimal violence may be done to our data by fitting it to a general unidimensional model. So long as we are aware that assumptions are being made in this approach that are not precisely correct, our informed violation of these assumptions should not mislead us.

However, if the aims of the researcher are more specific, such as testing specific hypotheses about attitudinal or affective correlates of specific behaviors--voting for union representation in NLRB elections or absenteeism on specific days or volunteering to work overtime--then more complex multivariate models are required. Similarly, if the aims of an

investigator are interventions designed to increase levels of job satisfaction in an organization, then, again, multi-dimensional models are required to provide evidence about which specific factors in the work situation should be changed. We can operate as researchers or practicioners with either model depending on our aims without making assumptions that we have learned much about specific causes of job satisfaction when we use a general factor approach or that we know much about the antecedents of behaviors reflecting general acceptance/rejection of a job when we use multivariate models.

The present authors would be the first to admit that a model of test-taking or questionnaire responding behavior should not be judged on its intuitive appeal, but rather on its usefulness for solving problems in the substantive areas of research. Thus far, the primary contribution of latent trait theory has been made in the area of aptitude testing. Some of the applications suggested in this area are tailored testing (Lord, 1970; Sympson, 1979); true score equating (Lord, 1977), and measuring the appropriateness of multiple choice test scores (Levine and Rubin, 1976; Levine and Drasgow, 1979). The reader is urged to consult the Spring issue of the Journal of Educational Measurment (1977) for a further description of applications and theory in this realm.

More specific to the assessment of job satisfaction, Parsons (1979) has shown that the measurement of appropriateness (Levine and Rubin, 1976) yields stable and predictable differences in the fit of a latent trait model of job satisfaction to samples of blacks and whites. Goldberg and Hulin (1979) have reported evidence of item bias in the JDI using the latent trait approach. Thus, the first steps have been taken in spite of the technical

problems in the estimation of parameters.

Other possible applications include the detection of invalid responses to questionnaire measures of job satisfaction through the use of appropriateness measurement (Parsons, 1979), and shortening the sample of items used through the choice of items that have the highest discriminating power at the expected levels of θ.

The utility of latent trait theory seems to have been demonstrated in the area of aptitude testing. This study has investigated a small aspect of the problem of generalizing latent trait theory to attitude assessments. The applicability and utility of latent trait theory in this latter area appears promising. Perhaps most importantly, this study has demonstrated the convergence of evidence from three quite different approaches to the study of the meaning of different item responses on job satisfaction questionnaires. Convergence among measures based on the first principal factor, on the general factor from a hierarchical factor model, and from a unidimensional latent trait model are encouraging. The results of this study provide some evidence for interpreting what is being estimated by 's derived from the JDI. Both the necessity and limitation of future developments stressing multidimensional latent trait theory in job satisfaction have been pointed out. Refinements of the model will generate more research aimed at specifying the usefulness of general and specific job satisfaction measures.

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Footnotes

2. This is not an exclusive characteristic of latent trait analysis. There are maximum likelihood estimation programs for factor analysis (Joreskog, 1970) and other methods of estimating latent trait parameters such as that of Urry (1978). The methods described and used in this paper probably are more frequently used though.

TABLE 1

Example of a Factor Pattern Matrix From Bi-Factor Solution

Item	Factor		
	G	1	2
1	.4	.5	
2	.4	.5	
3	.4	.5	
4	.4		.5
5	.4		.5
6	.4	.5	
7	.4		.5
8	.4		.5
9	.4	.5	
10	.4		.5

TABLE 2

First 10 Eigenvalues from 72 Item
JDI Correlation Matrix

Factor	Eigenvalue
1	11.06
2	3.97
3	3.63
4	2.45
5	2.18
6	1.41
7	.96
8	.90
9	.74
10	.62

TABLE 3
Correlations among Oblique Factors from
BINORMAMIN Rotation

	(1)	(2)	(3)	(4)	(5)
(1)	1.00				
(2)	.38	1.00			
(3)	.21	.18	1.00		
(4)	.38	.37	.30	1.00	
(5)	.23	.29	.38	.29	1.00
	(1)	(2)	(3)	(4)	(5)

TABLE 4

First Order Factor Loadings on
Second Order Factor

Factor	Loading
1	.555
2	.565
3	.469
4	.641
5	.524

TABLE 5
The Transformation Matrix

(1)	.555	.832	0	0	0	0
(2)	.565	0	.825	0	0	0
(3)	.469	0	0	.883	0	0
(4)	.641	0	0	0	.768	0
(5)	.524	0	0	0	0	.852
	(1)	(2)	(3)	(4)	(5)	(6)

TABLE 6

Item Discrimination Values (A_1), Principal Factor Loadings and Hierarchical Factor Loadings for JDI Items

Item (Work Scale)	A_1^*	PF	G	Loadings I	II	III	IV	V
Fascinating	.57	.37	33	-04	-05	09	43	03
Routine	.31	.27	23	-04	00	05	31	01
Satisfying	1.28	.50	43	01	-02	-05	56	09
Boring	.92	.44	38	01	-01	-05	48	10
Good	1.21	.41	34	06	06	-02	34	05
Creative	.57	.33	29	-05	-03	11	40	-02
Respected	.96	.47	40	06	02	03	38	07
Hot	.18	.18	14	10	06	-07	-01	14
Pleasant	.96	.45	38	12	05	-02	29	10
Useful	.87	.31	26	01	05	-06	34	00
Tiresome	.56	.37	32	05	00	-03	27	16
Healthful	.35	.26	22	02	04	09	11	07
Challenging	.83	.41	36	-03	-09	05	58	-04
On your feet	.01	.00	-01	03	01	-06	06	-08
Frustrating	.45	.30	25	12	01	00	07	19
Simple	.26	.14	13	-08	01	-05	29	-02
Endless	.30	.23	20	05	02	00	04	21
Gives sense of accomplishment	1.19	.49	42	00	-03	-01	58	01

$^*A_1$ = Item Discrimination Value

PF = Principal Factor Loadings

G = General Factor Loadings

TABLE 6 (Cont.)

Item (Pay Scale)	A_i	PF	G	I	Loadings II	III	IV	V
Income adequate for normal expenses	**	.33	.31	.01	−.02	−.01	.00	.52
Satisfactory profit sharing	**	.33	.32	−.03	−.01	−.08	.06	.57
Barely live on income	**	.43	.39	.02	.01	−.04	.06	.58
Bad	**	.26	.23	.02	.02	.04	.12	.13
Income provides luxuries	**	.19	.19	−.02	−.02	−.02	.03	.33
Insecure	**	.38	.34	.02	.07	.00	.08	.36
Less than I deserve	**	.33	.31	.00	.02	−.01	−.06	.57
Highly paid	**	.13	.14	−.06	−.08	.03	.04	.29
Underpaid	**	.38	.36	−.02	.02	.00	−.04	.63

**Item Discrimination Values were not computed for these items.

TABLE 6 (Cont.)

Items (Promotion Scale)	Loadings							
	A_1	PF	G	I	II	III	IV	V
Good opportunity for advancement	.62	.46	.37	.02	-.04	.78	.01	-.07
Opportunity somewhat limited	.40	.33	.27	-.01	-.01	.59	-.04	-.01
Promotion on ability	.60	.47	.38	.07	.04	.54	.05	-.04
Dead-end assignment	.63	.51	.42	.05	.02	.49	.10	.06
Good chance for promotion	.62	.48	.39	.01	-.02	.78	.04	-.09
Unfair promotion policy	.68	.49	.41	.11	.06	.29	.03	.20
Infrequent promotions	.46	.36	.30	.06	.02	.47	-.06	.06
Regular promotions	.51	.39	.32	.03	.00	.58	-.01	-.01
Fairly good chance for promotion	.65	.50	.40	.05	.02	.70	.02	-.06

TABLE 6 (Cont.)

Items (Supervisor Scale)	A$_i$	PF	G	I	Loadings II	III	IV	V
Asks my advice	.45	.36	.28	.28	-.07	.10	.15	-.02
Hard to please	.85	.48	.34	.60	-.05	-.01	-.03	.03
Impolite	.86	.42	.29	.59	-.03	-.02	-.07	-.01
Praises good work	.84	.45	.33	.45	-.04	.11	.04	-.02
Tactful	.74	.44	.31	.54	-.03	.07	-.01	-.08
Influential	.60	.49	.36	.38	.02	.15	.08	-.06
Up-to-date	.89	.53	.39	.50	.04	.07	.02	.00
Doesn't supervise enough	.53	.40	.29	.31	.10	.10	-.03	.01
Quick-tempered	.64	.35	.24	.55	-.01	.01	-.15	-.01
Tells me where I stand	.46	.36	.28	.30	-.07	.11	.09	.02
Annoying	1.101	.51	.36	.67	-.06	-.01	-.05	.03
Stubborn	.76	.42	.30	.55	-.03	-.02	-.09	.06
Knows job well	.75	.47	.34	.47	-.04	.03	.00	.01
Bad	1.19	.47	.34	.57	-.02	-.03	-.06	.04
Intelligent	1.01	.49	.35	.42	-.11	.03	.04	-.06
Leaves me on my own	.10	.32	.01	.13	-.02	-.10	.04	-.04
Around when needed	.71	.44	.33	.42	-.01	.03	.07	.00
Lazy	1.07	.38	.27	.47	-.01	-.04	-.04	.04

TABLE 6 (Cont.)

Items (Coworkers Scale)	A_i	PF	G	Loadings I	II	III	IV	V
Stimulating	.65	.42	.33	-.08	.37	.12	.16	-.07
Boring	.87	.43	.33	.00	.52	-.01	.00	.01
Slow	.70	.36	.28	-.07	.54	-.05	-.05	.07
Ambitious	.78	.39	.32	-.06	.36	.02	.13	.02
Stupid	1.05	.37	.28	.00	.51	-.05	-.03	-.01
Responsible	.91	.43	.34	-.05	.50	-.02	.07	.00
Fast	.61	.36	.29	-.08	.43	.03	.06	.00
Intelligent	1.01	.47	.36	.00	.47	.03	.12	-.09
Easy to make enemies	*	.39	.30	.02	.52	.05	-.10	-.02
Talk too much	.47	.42	.32	-.01	.41	.04	.15	-.11
Smart	.81	.38	.29	-.03	.56	-.04	-.05	.02
Lazy	.83	.34	.25	.04	.50	-.02	-.08	-.04
Unpleasant	.83	.35	.27	.08	.35	.02	-.08	.06
No privacy	*	.44	.35	-.05	.50	.04	.07	-.04
Active	.92	.43	.34	-.02	.44	.02	.06	.02
Narrow interests	.73	.43	.33	.03	.43	.02	.04	.00
Loyal	.80	.32	.24	.05	.44	-.02	-.09	.00
Hard to meet		.31	.24	.01	.40	.03	-.10	.05

TABLE 7

Intercorrelations of Item Discrimination Values, Principal Factor Loadings and Hierarchical Factor Loadings for 60 JDI Items

		(1)	(2)	(3)
(1)	A_i*			
(2)	PF	.89		
(3)	HF	.79	.77	

*A_i = Item Discrimination Values, PF = Principal Factor Loadings, HF = Hierarchical Factor Loadings.

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